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What is the probability of achieving the carbon dioxide emission targets of the Paris Agreement? Evidence from the top ten emitters

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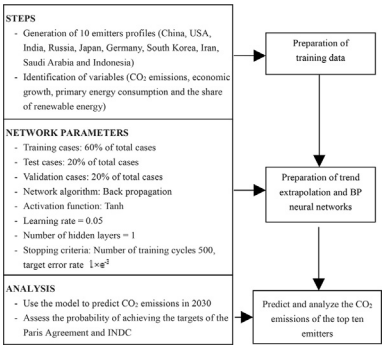
HIGHLIGHTS

- Probability of the TTCE achieving the Paris Agreement & INDC targets is predicted.
- CO_2 emissions in the TTCE in 2030 will increase by 26.5–36.5% compared with 2005.
- Parts of the TTCE can achieve INDC targets in some scenarios.
- Carbon reduction situations of Saudi Arabia, Iran and Indonesia are quite severe.
- No common trend can be used as a suitable benchmark for every country of the TTCE.

GRAPHICAL ABSTRACT


STEPS
- Generation of 10 emitters profiles (China, USA, India, Russia, Japan, Germany, South Korea, Iran, Saudi Arabia and Indonesia)
- Identification of variables (CO_2 emissions, economic growth, primary energy consumption and the share of renewable energy)
NETWORK PARAMETERS
- Training cases: 60% of total cases
- Test cases: 20% of total cases
- Validation cases: 20% of total cases
- Network algorithm: Back propagation
- Activation function: Tanh
- Learning rate = 0.05
- Number of hidden layers = 1
- Stopping criteria: Number of training cycles 500, target error rate $1\times e^{-3}$
ANALYSIS
- Use the model to predict CO_2 emissions in 2030
- Assess the probability of achieving the targets of the Paris Agreement and INDC
Preparation of training data
Preparation of trend extrapolation and BP neural networks
Predict and analyze the CO_2 emissions of the top ten emitters

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ABSTRACT

This study predicts the probabilities of achieving the carbon dioxide (CO_2) emission targets set by the Paris Agreement and the Intended Nationally Determined Contribution (INDC) of the top ten CO_2 emitters (TTCE). The TTCE are China, USA, India, Russia, Japan, Germany, South Korea, Iran, Saudi Arabia and Indonesia based on their emission trends over 1991–2015 period. The methods of trend extrapolation and back propagation (BP) neural networks are used in this paper to overcome the weakness of multiple linear regression (MLR) and the assumptions of the environmental Kuznets curve (EKC). The results show that the model performs well and has high predictive accuracy. The volume of the CO_2 emissions by the TTCE in 2030 is predicted to increase by 26.5–36.5%, compared with 2005. According to different trends of economic growth, energy consumption, and changes in share of renewable energy, the results show that China, India and Russia will achieve their INDC targets in some scenarios, whereas there will be a shortfall in achieving targets by USA, Japan, Germany, and South Korea. In particular, the carbon reduction situations of Saudi Arabia, Iran and Indonesia are quite severe. Moreover, the results show that there is no common trend that can be used as a suitable benchmark for every country for the implementation of carbon reductions targets of the Paris Agreement and their INDC goals. Finally, there are signs of improvement of the equality of carbon emissions based on the analysis of the Gini coefficient.

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1. Introduction

The Paris Agreement in December 2015 marked the ratification of the United Nations (UN) framework convention on climate change by

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over 160 contracting states. The participants agreed to achieve the long-term goal of restricting the increase in the global average temperature to less than 2 °C compared to the pre-industrial level and to pursue the limiting of global warming to 1.5 °C. Millar et al. (2017) found that the target of 1.5 °C is not yet a geophysical impossibility and net future cumulative CO_2 emissions will range from 250 GtC to 540 GtC. Although President Trump announced that the USA would cease all participation in the 2015 Paris Agreement, the earliest effective date of withdrawal for USA will be November 2020. In response to this announcement, governors of several states of USA formed the United States Climate Alliance to continue advancing the objectives of the Paris Agreement despite the federal withdrawal; similar commitments have also been expressed by other state governors, mayors, and business leaders (Cornwall, 2017).

In our study, we focus exclusively on China, USA, India, Russia, Japan, Germany, South Korea, Iran, Saudi Arabia, and Indonesia because of the unique characteristics of these countries. According to 2016 BP World Energy Statistics (BP Statistical Review of World Energy, 2016), these ten countries were ranked as the top ten CO_2 emitters (TTCE), responsible for over 68% global CO_2 emissions (Fig. 1). This study considered these ten countries an appropriate sample, based on not only their share of world CO_2 emissions, but also the absolute size of their CO_2 emissions, which were more than 600 million tonnes in 2015.

To achieve the global carbon emission reduction, countries have also come up with their own goals of Intended Nationally Determined Contribution (INDC) according to their own national conditions (see Table 1).

Most works of research investigating factors influencing CO_2 emissions reach the similar conclusion that economic growth and energy consumption should be taken into consideration (Jayanthakumaran et al., 2012; Ertugrul et al., 2016; Ahmad and Du, 2017; Ding and Li, 2017; Du et al., 2017; Zaman and Moemen, 2017). In recent years, the contribution of renewable energy to the decrease in CO_2 emissions is increasingly being acknowledged (Fernández González et al., 2014a; Fernández González et al., 2014b; Dellano-Paz et al., 2015; Liobikienė and Butkus, 2017). Besides, more and more countries are proposing policies and targets for renewable energy development, such as the Europe 2020 in the European Union (EU) and the 13th Five-Year Plan for Renewable Energy Development in China.

However, there is still a lack of analysis encompassing the Paris Agreement and INDC targets on CO_2 emission. For instance, Liobikienė and Butkus (2017) applied regression models to study whether EU-28 will successfully achieve the targets of Europe 2020 and Paris Agreement. Höhne et al. (2017) found that many of the INDCs are conservative, and in some cases, the achievement would exceed the targets. In this study, we expand the research by using BP neural network to analyse the extent to which the TTCE will achieve their carbon emissions targets, given their behavior, and especially considering the Paris Agreement and the INDCs.

This study makes a two-fold contribution to the literature. First, this study focuses on the TTCE and demonstrates that the BP neural network approach is well-suited to deal with multi-country time-series data in the field. Second, this study analyses 10 countries to provide empirical evidence on the probability of their achieving the CO_2 emission targets proposed in the Paris Agreement.

The rest of this paper proceeds as follows. Section 2 presents the literature review. Section 3 describes the methods used and Section 4 discusses the empirical results. Finally, Section 5 lists the main conclusions.

2. Literature review

2.1. Determinants of CO_2 emission and their impacts

Determinants of CO_2 emission and its effects have been extensively investigated in last few decades. Decomposition analysis is a commonly used method (Calbick and Gunton, 2014; Kaivo-oja et al., 2014; Zhao et al., 2016; Liobikienė et al., 2016; Zhao et al., 2017; Li et al., 2017), which includes mainly index decomposition analysis (IDA) and structural decomposition analysis (SDA). IDA can be further divided into

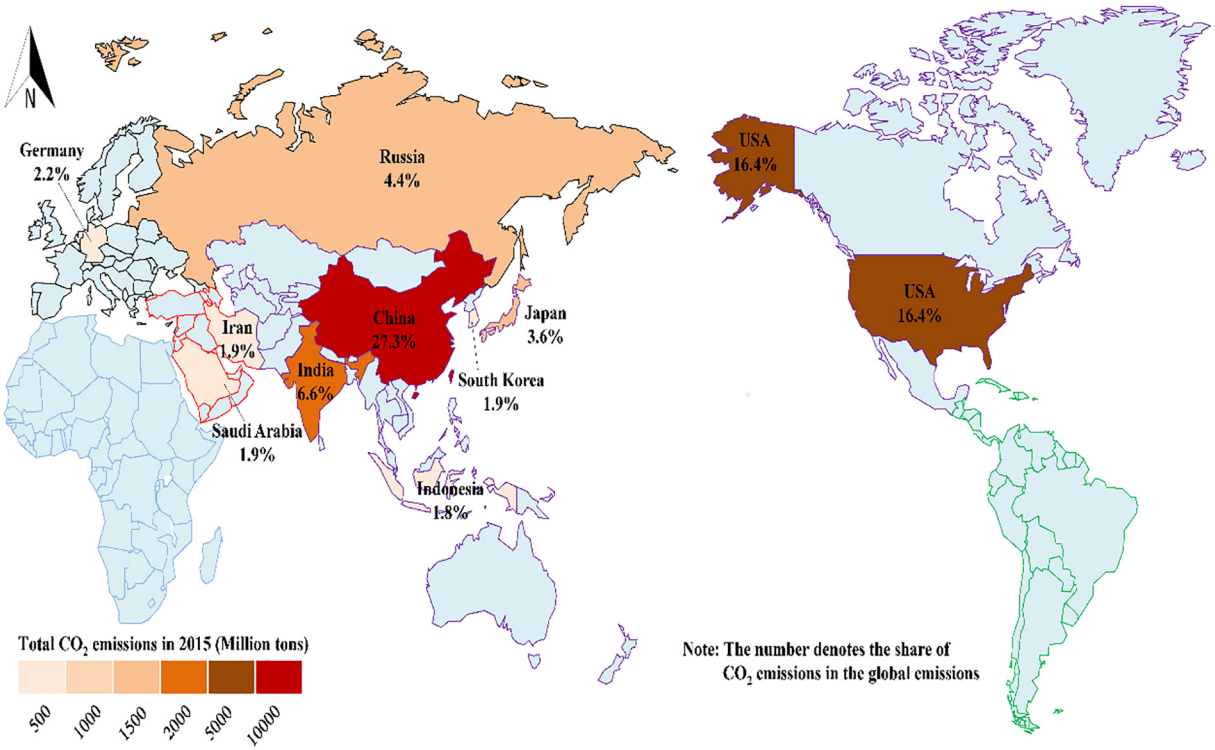

Fig. 1. TTCE: Geographic locations and proportion.
Data source: BP Statistical Review of World Energy, 2016.

Table 1
INDC goals of the TTCE.

Country	Target year	Base year	INDC goals
China	2030	2005	Reduce the CO_2 emissions per unit of GDP by 60–65%
USA	2025	2005	Reduce the greenhouse gas emissions by 26–28%
India	2030	2005	Reduce the CO_2 emissions per unit of GDP by 33–35%
Russia	2030	1990	Reduce the greenhouse gas emissions by 25–30%
Japan	2030	2013	Reduce the greenhouse gas emissions by 26%
Germany	2030	1990	Reduce the greenhouse gas emissions by 40%
South Korea	2030	–	Reduce the greenhouse gas emissions by 37% from the base scenario (business as usual, BAU)
Iran	N/a		
Saudi Arabia	N/a		
Indonesia	2030	–	Reduce the greenhouse gas emissions by 29% from the base scenario (business as usual, BAU)

Laspeyres IDA and Divisia IDA (Liobikienė et al., 2016), which are based on the basic Laspeyres and Paasche indices (Zhang et al., 2009) and the arithmetic mean Divisia index (AMDI) and logarithmic mean Divisia index (LMDI) (Ang et al., 2009; Fernández González et al., 2014b; Ding and Li, 2017), respectively. Meanwhile, SDA is based on input-output model (Guan et al., 2009; Jiang and Guan, 2016; de Vries and Ferrarini, 2017).

Other models are also employed, such as the Kaya identity (Padilla and Duro, 2013; Henriques and Borowiecki, 2017) and the IPAT identity (Saikku et al., 2008; Brizga et al., 2013; Zaman and Moemen, 2017). The Kaya identity combines four inputs-population, GDP per capita, energy intensity, and carbon emission per unit of energy consumed-to estimate the total greenhouse gas (GHG) emission levels (Kaya and Yokobori, 1993). The IPAT framework uses three factors to explain GHG emissions impacts: growth of population (P), affluence (A), and technology (T) (Ehrlich and Holdren, 1972).

There is consensus that economic growth and energy consumption should be taken into consideration when it comes to CO_2 emission reduction (Jayanthakumaran et al., 2012; Ertugrul et al., 2016; Ahmad and Du, 2017; Ding and Li, 2017; Du et al., 2017; Zaman and Moemen, 2017). The other most influential factors that are most frequently discussed in the previous studies include population (Brizga et al., 2013; Kaivo-oja et al., 2014; Calbick and Gunton, 2014; Ahmad and Du, 2017), investment (Zhao et al., 2016; Ahmad and Du, 2017), trade openness (Yang and Zhao, 2014; Ertugrul et al., 2016; Ahmed et al., 2017), technological factors (Calbick and Gunton, 2014; Du et al., 2017; Li et al., 2017; Yang and Li, 2017), and industrial structure (Calbick and Gunton, 2014; Du et al., 2017). However, the results are still somewhat ambiguous and divergent; for example, there is no clear understanding of the influence of trade openness on CO_2 emission levels. Jalil and Mahmud (2009), Jayanthakumaran et al. (2012), Farhani et al. (2014), and Al-Mulali et al. (2015) revealed that trade openness should have no impact on CO_2 emissions while Ertugrul et al. (2016) and Onafowora and Owoye (2014) pointed out that it has both positive and negative impacts, depending on the country. Specially, the important role of renewable energy in the reduction of CO_2 emissions has been gaining greater attention in recent years (O'Mahony et al., 2013; Liobikienė et al., 2016; Sugiawan and Managi, 2016; Liobikienė and Butkus, 2017).

Based on the above studies, we focus on two basic determinants, that is, economic growth and energy consumption (in line with Jayanthakumaran et al., 2012; Ertugrul et al., 2016; Ahmad and Du, 2017; Ding and Li, 2017; Du et al., 2017; Zaman and Moemen, 2017). We also consider the role of renewable energy.

In terms of methods, regression models (Calbick and Gunton, 2014; Alshehry and Belloumi, 2016; Ahmad and Du, 2017; Liobikienė and Butkus, 2017; Ouyang and Lin, 2017) and environmental Kuznets curve (EKC) (Jalil and Mahmud, 2009; Ertugrul et al., 2016; Sugiawan and Managi, 2016; Zaman and Moemen, 2017; Yang et al., 2017) are usually applied to reveal how the factors change CO_2 emissions. However, the assumptions of EKC have never received strict verification with a large available data set, and therefore, it may be inappropriate to describe the relationship (Yang et al., 2015). Empirical evidence from EKC did not arrive at a consensus (Alam et al., 2016). For example, Ben Jebli et al. (2016) studied data for 25 Organization for Economic Co-operation and Development (OECD) countries, Arouri et al. (2012) for 12 Middle East and North African countries, and Musolesi et al. (2010) for 106 developed and developing countries, but did not find any evidence supporting the EKC hypothesis.

The aim of this study is to predict the probability of the TTCE achieving the Paris Agreement climate policy targets. Grossman and Krueger (1994) revealed that there is a nonlinear relationship between economic growth and environmental degeneration. There is no universal model fitting every country (Yang et al., 2015) but neural networks could be used for "categorization and….prediction problems when inputs are related in nonlinear ways," (Garson, 1998) which is very helpful in dealing with the time-series data for TTCE. Neural networks outperform traditional statistical methods (Szoplik, 2015), especially when inputs and constraints are related in complex, nonlinear ways (Gorsevski et al., 2016; Yesilnacar and Topal, 2005). Thus, we combine the trend extrapolation model and BP neural networks to implement simulation process and obtain the prediction results of CO_2 emissions for the TTCE in 2030. That is, the trend extrapolation model is used for the generation of future values of exploratory variable (input data) (Liobikienė and Butkus, 2017) for the BP neural network.

2.2. CO_2 emissions of TTCE and the Paris Agreement

There are several studies on one or more of the TTCE that use different econometric methods and models, which bring scattered results and show scarce conclusive evidence on the TTCE. As the world leader in CO_2 emissions, China is thought to play a key role in climate change mitigation (Du et al., 2017; Li et al., 2017; Mi et al., 2017). The changes in China's CO_2 emissions and the factors influencing them at the national, provincial, or city level have been widely discussed (Fan et al., 2007; Dhakal, 2009; Tian et al., 2013; Du et al., 2014; Ouyang and Lin, 2015).

Russia will reach the turning point in ten years if its economic growth rate remains stable (Yang et al., 2017). Assuming an annual increase of 5%, Mirzaei and Bekri (2017) predicted that the total CO_2 emissions in Iran will reach 985 million tonnes in 2025. Alshehry and Belloumi (2016) asserted that economic growth cannot continue in Saudi Arabia without continuous increases in carbon emissions. Findings about the rapid growth of CO_2 emissions in India and Indonesia were also presented (Yang and Zhao, 2014; Sugiawan and Managi, 2016; Alam et al., 2016).

Several previous works have discovered the existence of somewhat similar trends of CO_2 emissions in different groups of countries. Henriques and Borowiecki (2017) found evidence for rise in emissions in Denmark, France, Germany, Italy, the Netherlands, Portugal, Spain, Sweden, the UK, the United States, Canada, and Japan; the study by Ahmed et al. (2017) indicated a rising trend in five South Asian countries-India, Pakistan, Bangladesh, Nepal and Sri Lanka; that by

Behera and Dash (2017) suggesting 17 countries in the South and Southeast Asian region; that by Ertugrul et al. (2016) found emissions rising in developing countries, such as Thailand, Turkey, India, Brazil, China, Indonesia and South Korea. Similarly, the study by Deviren and Deviren (2016) confirmed the growth in emissions in the 33 countries it covered; that by Yang et al. (2015) did so by sampling 67 countries; Kaivo-oja et al. (2014) got a similar result by studying China, EU-27 and USA; finally, those by Fernández González et al. (2014a) and Liobikienė and Butkus (2017) confirmed it for EU-28. Meanwhile, there are also some studies highlighting the difference in emission figures, such as the study by Calbick and Gunton (2014) on the differences among OECD countries' GHG emissions.

In the former set of literatures, the similarities in emission figures were interpreted to derive from economic globalisation, which directs the production processes of businesses to develop in similar patterns (Kaivo-oja et al., 2014; Ouyang and Lin, 2017). Meanwhile, the differences might be caused by the difference in structures (Kaivo-oja et al., 2014), existing technologies (Calbick and Gunton, 2014), or economic development levels (Yang et al., 2015).

There is still a lack of analysis that encompasses the Paris Agreement and INDC targets on CO_2 emission, especially one that highlights the important roles of the main emitters. Therefore, this paper is significant in expanding the research in this field.

3. Methodology

3.1. Forecasts of input variables

In this paper, we aim at analyzing the probability of the TTCE achieving the Paris Agreement climate policy targets. First, when taking CO_2 emissions, primary energy consumption and the share of renewable energy into consideration, three trend scenarios based on past experiences are set, according to three different time windows (Liobikienė and Butkus, 2017): the 1991–2015 period (long period), which reveals all the changes in variables during the entire period, the 2000–2015 period (inter-medium period), which covers the changes in variables during the entire economic cycle including economic growth, decline, and recovery; and the 2010–2015 period (short period), which reflects the recent changes in variables, the recent situation after the adoption of some CO_2 reduction policy of the TTCE, and 2010 as the base level for expressing results in constant currency terms. Further, the prediction accuracy can be strengthened considerably because we adopt three different trend scenarios based on past experiences to make full use of past information.

The statistical technique of trend extrapolation, which is a basic approach to make and justify statements about trends in the time series data, is applied to predict the variables (primary energy consumption and the share of renewable energy) by relating them to the occurring time. The following are the two assumptions: (1) there is no drastic change in the development of the analysed variables; (2) if factors determining CO_2 emissions change during 2015–2030 period, similar changes will take place in average CO_2 emissions during the three period windows-long, inter-medium, and short. By drawing the scatter diagrams, as well as observing and comparing their changing trends with different kinds of function curve models, the linear model was selected for trend extrapolation. Its general form is as follows:

$$y_{ti} = \beta_0 + \beta_1 t + u_t \tag{1}$$

where y_{ti} represents primary energy consumption (in million tonnes of oil equivalent) and the share of renewable energy (expressed as a % of total energy consumption) in the year t for the country i. The most commonly used least squares fitting procedure is used. The trends in primary energy consumption and the share of renewable energy till 2030 will keep developing, as will those of average CO_2 emissions, during the three period windows.

The average growth rate of the economy from 1991 to 2015, 2000–2015, and 2010 to 2015 is taken as the growth rate during the periods. The change in GDP is also based on such assumptions instead of using trend extrapolation (Liobikienė and Butkus, 2017).

3.2. Probabilities of the TTCE achieving targets set during the Paris Agreement

To evaluate the probabilities of the TTCE emitters achieving targets of the Paris Agreement, we apply the BP neural network model to the data from 1991 to 2015 for these 10 emitters.

Neural networks outperform traditional statistical methods, especially when inputs and constraints are related in complex, nonlinear ways (Gorsevski et al., 2016; Yesilnacar and Topal, 2005). Feed-forward back-propagation (BP) is a well-known learning algorithm for training neural networks, which can supplement existing theoretical analyses and decision-making processes. That is, BP neural network model is one of the most commonly used and most mature artificial neural network models (Bode, 2000; Olabi et al., 2006; Yu et al., 2008; Saljooghi and Hezarkhani, 2015; Sun and Xu, 2016). Information processing is divided into forward data calculation and back learning (namely the BP of error signals and correction of relative values) to approximate a given expected output. A trained network can be used to predict the target variable. This method is believed to be most applicable for simulating the correlation of inputs and outputs (Fan, 2007). Funahashi (1989) proved that the three-layer network with only one hidden layer is sufficient to express any continuous function with the required accuracy, assuming an adequate number of hidden layer nodes. The artificial neural network can estimate any function in a broad category and reveal the nonlinear relationship that exists in the data sample (Hornik et al., 1990; Zhang and Wu, 2009; Dong et al., 2017a).

Suppose that the number of input layer neurons is n; the number of hidden layer neurons is p; and the number of output layer neurons is m. Thus, we can infer a training process described by the following equations, which can be divided into two steps:

Step 1: Hidden layer stage. The output of the hidden layer neurons can be calculated as follows:

$$x_i^1 = f\left(\sum_{j=1}^{n} w_{ij}^0 x_j + w_{i0}^0\right), i = 1, 2, \ldots, p \tag{2}$$

where $\sum_{j=1}^{n} w_{ij}^0 x_j + w_{i0}^0$ represents the weighted sum of n input layer neurons; w_{ij}^0 is the weight coefficient reflecting the influence level of the input layer neuron j on the hidden layer neuron i; w_{i0}^0 is the threshold value of the hidden layer neuron i; and $f(x)$ is a non-memory nonlinear excitation function used to change the output of neurons.

Step 2: Output layer stage. Similarly, the output of the output layer neurons is:

$$y^k = f\left(\sum_{j=1}^{p} w_{jk}^1 x_j^1 + w_{k0}^0\right), k = 1, 2, \ldots, m \tag{3}$$

Moreover, the error function of neurons in the output layer is defined as:

$$E = \frac{1}{2}\sum_{k}\left(d^k - y^k\right) \tag{4}$$

where d^k is the target value. The error value at every node in the former

layer is calculated layer-by-layer by using BP and corrected by using the following weighted correction formula:

$$\Delta w_{ij}^{m} = \eta \delta_j^m y_i^{m-1} \tag{5}$$

where η is the learning rate and δ_j^m is the error signal.

That is the case in our analysis, and so we set the CO_2 emissions as the output, whereas primary energy consumption, the share of renewable energy, and economic growth are used as the inputs.

Prior to these steps, data should be normalized to overcome problems arising from different physical significances and dimensions of the input and output data. Since we use a Tanh activation function, we choose the interval $[-1, 1]$ for normalization purposes. The following formula is commonly used:

$$P_i = 2 \times \frac{I_i - I_{min}}{I_{max} - I_{min}} - 1 \tag{6}$$

where I_i represents the input or output data, and I_{min} and I_{max} are the minimum and maximum values, respectively, of input and output data.

We train the constructed BP network model using the MATLAB neural network toolbox. Taking early stopping into consideration, we randomly divide the samples into training (60%), validating (20%), and testing (20%) subsamples. The target error requirements are satisfied for these different situations through the MATLAB simulation, and the BP algorithm is found to have reliable basis, discrete derivation, high accuracy, and strong universality as its features. We adopt the improved Levenberg–Marquardt (L-M) algorithm that combines the gradient descent method and the Gauss-Newton algorithm, where the "tansig" function is used as the transfer function, and the "train lm" function is used as the training function. We use a 500-cycle training process with a 5% learning rate and target error of $1 \times e^{-3}$. To ensure the accuracy and the ability of the prediction model to generalize, one of the trained neural networks (when the correlation coefficients between the output and target values for the different parts of samples are all above 0.9 and close to 1, that is, it is completely trained) is used to first predict the values of CO_2 emissions for the years in the 1991–2015 period; the results of the comparison for these is discussed in the next section. Then, the forecast values for the TTCE in three scenarios are compared with the target values.

Renewable energy in our study includes hydro, solar, wind, geothermal and biomass energy. The data for CO_2 emissions, primary energy consumption, and the share of renewable energy are taken and calculated from the 2016 BP World Energy Statistics. The amount of renewable energy is equal to the sum of hydro, solar, wind, geothermal, and biomass energy. The percentages share of renewable energy in the total volume of energy is calculated as the share of renewable energy. The data for GDP (constant 2010 US$) are from the World Bank database.

4. Results and discussion

4.1. Results of input variables forecasts

The extrapolated changes in factors influencing CO_2 emissions in the three scenarios are presented in Table 2.

Before the advent of the Paris Agreement climate policy, differences in the changes in CO_2 emissions of the TTCE are observed at the country level and in separate periods. As for a long term (1991–2015), CO_2 emissions decreased only in Russia and Germany, but increased in the other countries, with the highest annual increase-of over 5%-being observed in Indonesia, China, and India. This was mostly related to the fact that these three developing countries experienced rapid economic development, and thus, a huge increase in CO_2 emissions (Dong et al., 2017b, 2017c). A high annual increase, of over 4%, also existed in Iran and Saudi Arabia, two petroleum-rich countries (see Fig. 2).

In the 2000–2015 period, a decrease in CO_2 emissions was observed only for USA, Japan, and Germany; in the 2010–2015 period, such a decrease only took place in USA, Russia, and Germany. To summarize, a decrease in the average annual rate of CO_2 emissions was for Germany, irrespective of the period analysed, which might indicate the effect of a relatively more active climate policy in Germany. Further, emissions by the USA had an annual increase rate during the long period (1991–2015), the largest decrease rate during 2010–2015, and a medium decrease during 2000–2015 (Fig. 2).

During 1991–2015, primary energy consumption grew in most of the TTCE, except Russia and Germany, which coincided with a decrease in CO_2 emissions in these two countries in the same period. The highest average annual growth rate (5.2–6.2%) was observed in China, Indonesia, and India (see Fig. 3). In the inter-medium period, primary energy consumption decreased in USA, Japan, and Germany. Meanwhile, the energy consumption decrease was the most dramatic during the short period because of significant contributions made by four countries (USA, Russia, Japan, and Germany). The largest average annual decrease of −2.05% was achieved by Japan; this can be attributed to the continuous efforts made for energy efficiency improvement using technological innovation. Japan has successfully shifted from the manufacture of energy-intensive products to high-technology and knowledge-intensive ones (Warr et al., 2010). Meanwhile, the carbon footprint and carbon reduction in Japan have also been explained by the industrial symbiosis witnessed in recent years (Hashimoto et al., 2010; Dong et al., 2014). Another big contributor, Germany, succeeded in reducing energy consumption by adjusting its production structure (Fernández González et al., 2014a).

The renewable energy share (RES) in the total energy consumption by Saudi Arabia is zero. Declines in RES occurred only in India and Iran in the 1991–2015 period, in Russia in the 2000–2015 period, and in Indonesia in the 2000–2015 and 2010–2015 periods. In China, USA, India, Japan,

Table 2
Assumptions about trends of economic growth, energy consumption, and share of renewable energy in 2015–2030.
Data source: Adapted from the BP Statistical Review of World Energy (2016).

	Economic growth in percent			Change of energy consumption in percent			Change of share of renewable energy in percent		
	1991–2015	2000–2015	2010–2015	1991–2015	2000–2015	2010–2015	1991–2015	2000–2015	2010–2015
China	9.99	9.65	7.87	6.17	7.61	3.92	4.18	4.97	7.89
USA	2.56	1.79	2.09	0.62	−0.09	−0.04	1.31	3.28	5.55
India	6.77	7.18	6.74	5.24	5.45	5.30	−1.11	0.54	0.91
Russia	0.78	3.59	1.17	−1.03	0.48	−0.19	1.09	−0.28	0.38
Japan	0.89	0.75	0.98	0.03	−0.89	−2.05	1.64	4.08	7.76
Germany	1.32	1.13	1.58	−0.28	−0.25	−0.19	11.19	12.23	13.54
South Korea	4.77	3.93	2.96	4.29	2.56	1.70	0.22	3.49	8.38
Iran	2.40	2.51	−2.64	4.97	5.00	3.24	−0.70	5.82	10.25
Saudi Arabia	3.92	5.06	5.00	4.83	5.58	4.09	–	–	–
Indonesia	4.72	5.33	5.51	5.34	4.57	5.62	0.52	−0.61	−5.59

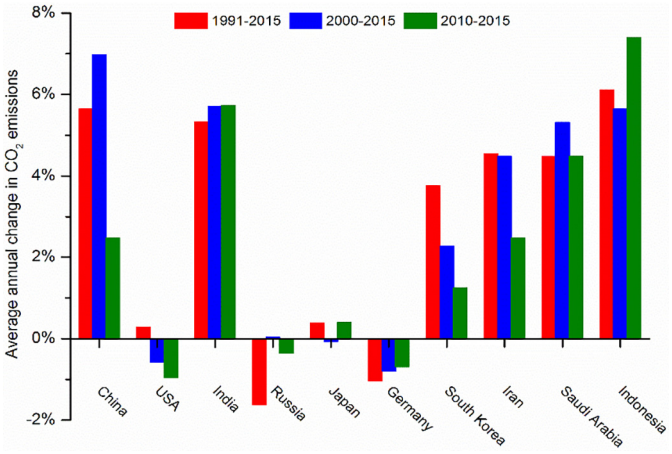

Fig. 2. Average annual changes in CO_2 emissions.

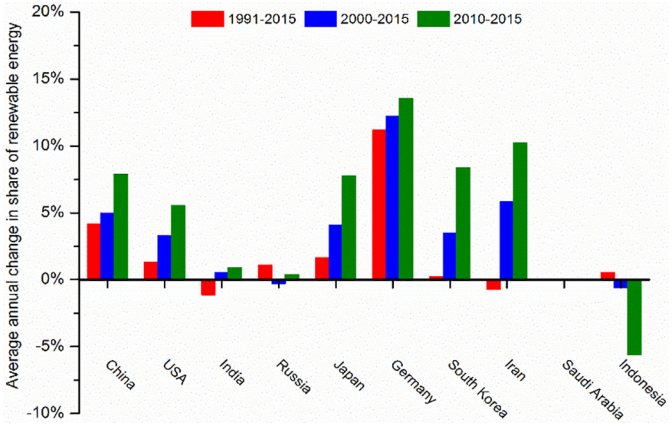

Fig. 4. Average annual changes in the share of renewable energy.

Germany, South Korea and Iran, the 2010–2015 period was the most successful in achieving the growth of RES. For Russia and Indonesia, RES increased significantly during the 1991–2015 period (Fig. 4). Meanwhile, Germany lead in the growth rates in RES during all the three periods, registering growth above 10%. In Germany, the considerable increase in renewable energy generation in recent decades has helped in the growth in RES (Dellano-Paz et al., 2015; Jägemann et al., 2013).

Forecasts of primary energy consumption, RES, and GDP in 2030, taking the average trends of three different periods (long, inter-medium, and short) into account, are used as input data for the following BP neural network, as shown in Tables A1–A3.

4.2. CO_2 emissions forecasts for 2030 based on BP neural network

Before using the trained neural network to predict CO_2 emissions in 2030 directly, we first implement the "forecasts" of CO_2 emissions for the years in the 1991–2015 period and present the detailed results by comparing these with the actual values in Fig. 5.

As shown in Fig. 5, the error between the prediction output values and the actual values is minimal. The trained neural network can be used as a prediction tool because the error between the "prediction" output values of BP neural network model and the actual values are well below the accepted threshold of 10% (Du et al., 2008).

Forecasts of CO_2 emissions in 2030, taking the average trends of three different periods-long, inter-medium, and short into account, are shown in Table 3.

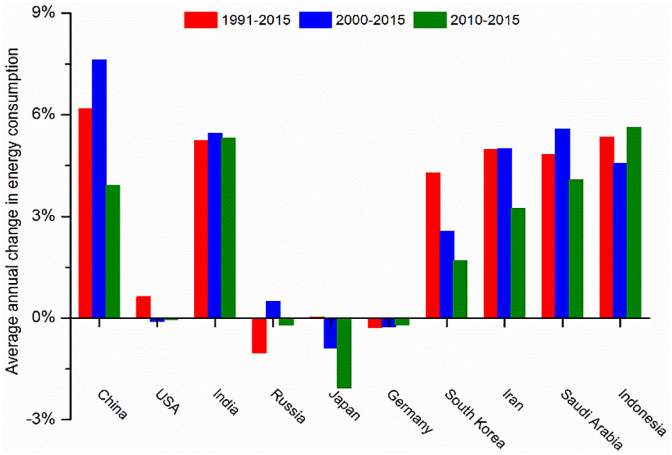

Fig. 3. Average annual changes in primary energy consumption.

As shown in Table 3, the combined CO_2 emissions in these ten countries in 2030 are predicted to be 26.5–36.5% more than that in 2005. In terms of the percentage change in CO_2 emissions, India, Indonesia, and Saudi Arabia are no doubt at the top of the increase in carbon emissions list (the percentage growth of their CO_2 emissions are either greater than or equal to 100%), followed by China, Iran and South Korea. Meanwhile, Germany is anticipated to do better in reducing carbon emissions.

The carbon reduction situation in Saudi Arabia and Iran is grim, but they have not committed themselves to any INDC goals, which would cause international attention and discussion in the future. As for USA, the CO_2 emission is predicted to decrease by 16.6% in 2030, compared with 2005 based on the inter-medium period trends, which illustrates that there exists a gap with the targeted carbon reduction of 26–28%. Since the INDC goals for countries is based on the BAU scenario, the reduction target of 29% and 37% for Indonesia and South Korea, respectively, are relatively lax. Indonesia, in particular, is less likely to have a desired behavior in carbon reduction.

To compare the forecast values with the INDC goals for the TTCE (see Table 1 above) in a way that is appropriate and reasonable, more calculations are needed. China is predicted to reduce its CO_2 emissions per unit of GDP in 2030 by 49.0%, compared with the value in 2005, based on the long period trend; this reduction is less than the target stipulated in the Agreement. However, the reductions of 66.3% and 68.9% in the short period and inter-medium period, respectively, exceed the target. Similarly, the inter-medium period trend for India suggests that will reduce the CO_2 emissions per unit of GDP in 2030 by 32.7%, compared with the figure in 2005, and thus, come close to meeting its INDC target. However, the reductions of 23.9% and 18.7%, in the short period and long period, respectively, are less than the target. Russia and Germany both set 1990 as the base year. As per the predictions, Germany is expected to reduce the CO_2 emissions by about 30% in 2030, compared with those in 1990, which means that it will fall short of its INDC target by 140%. For Russia, the reductions can exceed the INDC target, based on the short and long period trends. As for Japan, setting 2013 as base year, the change in CO_2 emissions is predicted to range from −5.5% to 1%. This shows an uncertain prospect for the achievement of its INDC target (40% reduction).

Further, we end up modeling the CO_2 emissions by trying to answer the following question: although most countries have set reduction targets, is the allocation of national CO_2 reduction targets reasonable? Based on the actual data of 2015 and the future scenarios predicted by this study, we use the Lorenz curve and Gini coefficient to visualize inequality in CO_2 emissions across the TTCE. The Gini coefficient was firstly developed by the Italian economist Gini at the beginning of the 20th century. It is based on the Lorenz curve and determines the level of

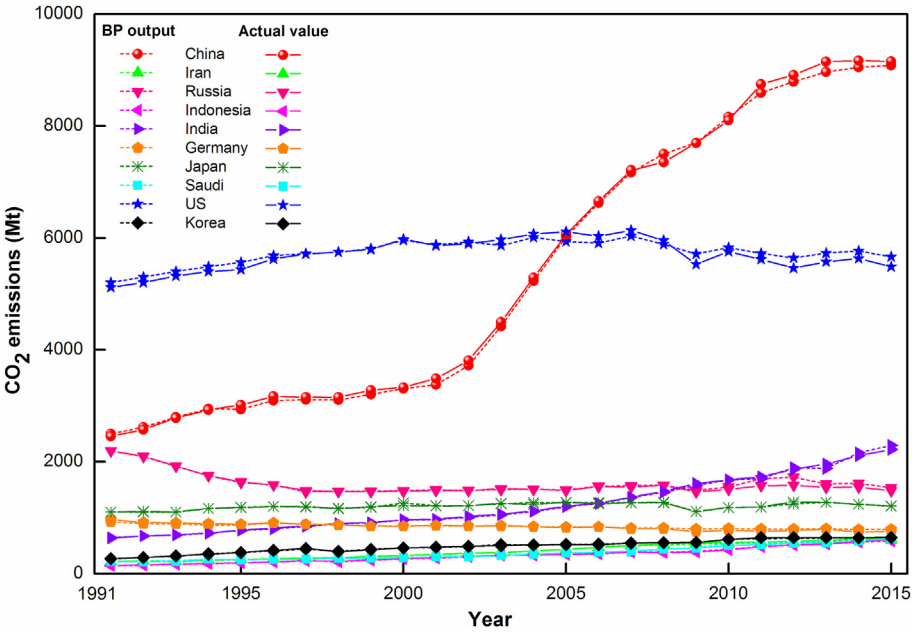

Fig. 5. Comparison between results of the model for the TTCE in terms of "predicted" emissions and the actual data during the 1991–2015 period.

income equality among residents. This approach is data-driven and easy to understand, and allows inter-country comparisons (Kammen and Kirubi, 2008). Fig. B1 displays the Lorenz curve for CO_2 emissions. The distribution curve of 2015 closely tracks the forecast curve which is based on the long period trend. The inequality measures of these curves yield Gini coefficients of 0.3670 and 0.3701 for the distribution curve and forecast curve, respectively. The distribution of forecasts of CO_2 emissions in 2030, based on the trends for short and medium periods are skewed much more toward the equality line. The Gini coefficient for the short period and medium period, are 0.2962 and 0.2761, respectively, which are their lowest level. In short, according to the short- and medium-term trends in this paper, there are indeed signs of improvement of the equality of carbon emissions.

5. Conclusions

As the public concerns about the increasing CO_2 emissions grow, controlling and mitigating CO_2 emissions have become a priority for global economic development. This study reveals the probabilities of the TTCE to achieving the reduction targets set during the Paris Agreement and the INDC targets, based on their trends observed over the 1991–2015 period. The results show that the methods of trend extrapolation and BP neural networks perform well and have high predictive accuracy. The total volume of CO_2 emissions by the TTCE in 2030 is predicted to increase by 26.5–36.5%, compared with the value in 2005. According to different trends of economic growth, energy consumption, and share of renewable energy changes, the results show that parts of the TTCE (China, India and Russia) will achieve their INDC targets in some of the scenarios considered, while a shortfall is likely for USA, Japan, Germany, and South Korea. In particular, the carbon situations of Saudi Arabia, Iran, and Indonesia are quite severe, but they have not committed themselves to any of the INDC goals, which would cause international attention and discussion in the future.

When taking CO_2 emissions, primary energy consumption, and the share of renewable energy into consideration, three trend scenarios based on past experiences are set according to three different period windows-long, medium and short. The results show that there is no trend that can be used as a suitable benchmark for the implementation of carbon reductions targets of the Paris Agreement

Table 3
Forecasts of CO_2 emissions in 2030.

	Predicted CO_2 emissions (million tons) based on the trends of:			CO_2 emissions (million tons) in 2005	Predicted CO_2 emissions compared with 2005 (decrease −/increase +)		
	1991–2015	2000–2015	2010–2015		1991–2015	2000–2015	2010–2015
China	10,405.5	9001.0	10,878.7	6058.3	71.8%	48.6%	79.6%
USA	6001.3	5094.9	5289.9	6108.2	−1.8%	−16.6%	−13.4%
India	2632.5	2688.5	2546.3	1209.3	117.7%	122.3%	110.6%
Russia	1481.7	1891.7	1468.9	1489.4	−0.5%	27.0%	−1.4%
Japan	1288.7	1277.1	1206.3	1278.0	0.8%	−0.1%	−5.6%
Germany	704.5	699.5	700.2	822.1	−14.3%	−14.9%	−14.8%
South Korea	701.2	698.5	689.1	521.2	34.5%	34.0%	32.2%
Iran	723.2	753.2	649.3	436.9	65.5%	72.4%	48.6%
Saudi Arabia	738.0	744.0	714.1	370.2	99.4%	101.0%	92.9%
Indonesia	724.8	730.1	742.3	341.5	112.2%	113.8%	117.4%
Total	25,401.3	23,578.5	24,885.1	18,635.1	36.3%	26.5%	33.5%

and their INDC goals of every country. However, there are signs of an improvement in the equality of carbon emissions, based on the analysis of the Gini coefficient.

By the way, we recommend renewable energy can be regarded as an effective alternative to fossil fuels. For developing countries, such as China and India, it will be all the more necessary to accelerate development of renewable energy industry to resolve the change in CO_2 emissions. An adjustment in the energy consumption structure is an urgent requirement to achieve the win-win combination of CO_2 reduction and economic growth, especially for petroleum-rich countries, such as Saudi Arabia and Iran. Therefore, planning for, and increasing the use of renewable energy is expected to promote the sustainable development of countries in the future.

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Appendix A

Table A1
Forecasts for primary energy consumption in 2030.

	Predicted primary energy consumption (million tonnes oil equivalent) based on the trends of:		
	1991–2015	2000–2015	2010–2015
China	4554.03	5387.76	4604.20
USA	2516.26	2217.89	2339.56
India	937.66	1081.30	1179.94
Russia	615.61	756.27	657.22
Japan	486.08	391.58	317.14
Germany	304.02	289.76	314.96
South Korea	395.55	375.78	332.93
Iran	391.34	414.95	384.02
Saudi Arabia	358.94	412.23	403.87
Indonesia	263.27	276.87	331.01

Table A2
Forecasts for RES in 2030.

	Predicted share of renewable energy based on the trends of:		
	1991–2015	2000–2015	2010–2015
China	11.54%	14.13%	21.82%
USA	5.83%	8.31%	9.13%
India	7.00%	7.89%	8.48%
Russia	6.25%	5.17%	6.97%
Japan	8.31%	9.24%	15.02%
Germany	17.80%	23.05%	31.14%
South Korea	0.64%	1.27%	1.83%
Iran	0.67%	1.47%	3.35%
Saudi Arabia	0	0	0
Indonesia	3.40%	3.74%	1.07%

Table A3
Forecasts for GDP in 2030.

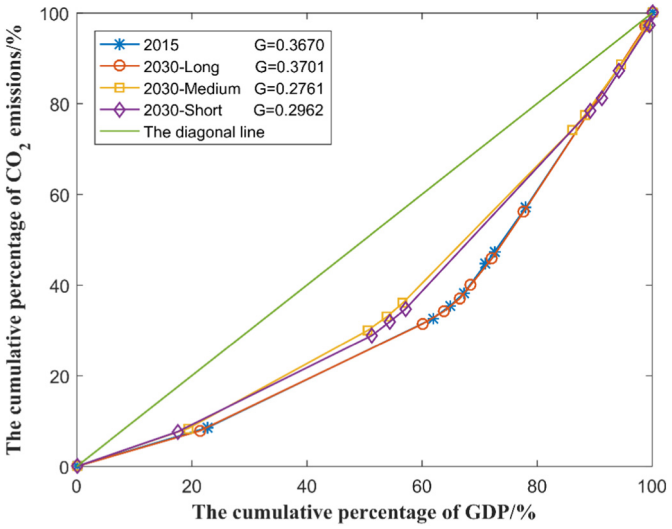
	Predicted GDP (constant, 2010 prices, US$) based on the trends of:		
	1991–2015	2000–2015	2010–2015
China	1.2E + 13	1.7E + 13	1.9E + 13
USA	2.1E + 13	1.8E + 13	2.0E + 13
India	3.0E + 12	3.7E + 12	3.1E + 12
Russia	2.0E + 12	2.5E + 12	1.8E + 12

Table A3 (*continued*)

	Predicted GDP (constant, 2010 prices, US$) based on the trends of:		
	1991–2015	2000–2015	2010–2015
Japan	7.0E + 12	6.6E + 12	6.4E + 12
Germany	4.6E + 12	4.6E + 12	4.0E + 12
South Korea	2.0E + 12	1.9E + 12	1.6E + 12
Iran	6.0E + 11	6.0E + 11	3.0E + 11
Saudi Arabia	1.0E + 12	1.2E + 12	1.2E + 12
Indonesia	1.5E + 12	1.6E + 12	1.8E + 12

Appendix B

Fig. B1Lorenz curve of CO_2 emissions with the GDP on *X* axis. The diagonal represents the line of perfect equality.



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